SYSTEMATIC MATHEMATICAL MODELING FOR SHORT TERM INDOOR ROOM TEMPERATURE FORECASTING IN SMART ENVIRONMENT: EVIDENCE FROM INDIA

SYNOPSIS

The rapid population surge and urbanization in developing countries like India has led to unprecedent energy requirements, particularly in the residential and corporate building structures. Hence, the energy prediction and subsequent energy optimization of building structures has gained importance to check unnecessary energy wastage and minimize carbon emissions. There is a growing fear that, if energy consumption is not controlled, it will result in energy shortfall (Shah *et al*., 2019). To overcome this expected future energy shortfall, there are two options: 1) Increased energy production and 2) Minimize energy consumption by checking energy wastage. While increasing energy production is a costly option, owing to the availability of limited resources, reducing energy wastage using some pro-active and pre-emptive measures or tools is achievable (Shah *et al*., 2019).

A 'Smart Building' (Buckman *et al.*, 2014) integrates the intelligence, control, construction material and resourcefulness of the entire building structure, with adaptability, in such a manner that it meets the building progression drivers like energy efficiency, comfort level, longevity and satisfaction levels. In recent years, residential and corporate building structures all over the world are adopting smart technologies for efficient energy management. The Energy Statistics report from the Ministry of Statistics and Programme Implementation,

Government of India, suggests that in the year 2017-18, building sector's energy consumption of India accounted for one-third of the total energy consumption. Out of total energy consumption of 1,130,244 GWh (year 2017-18) of electricity, the residential buildings sector accounted for 273,550 GWh (24.2%), whereas for the commercial buildings sector, this figure stood at 96,141 GWh (8.5%) (The Energy Statistics, India, 2019). Another report from the Indian Bureau of Energy Efficiency (BEE) suggests that about 80% of the total energy consumed in commercial building structures accounts for lighting, heating, and cooling systems. BEE has suggested that, in a typical office building structure, applying certain measures, such as improved insulation, usage of high-efficiency electrical appliances and, with proper review and adjustment of Heating, Ventilation and Air-Conditioning (HVAC) systems, energy consumption per unit area can be reduced efficiently. BEE has projected a target of reduction of the building energy consumption by 55%, which in turn, can help in cutting 150 million tonnes of carbon emissions by the year 2030 (BEE Report, 2020). To meet these committed targets, various Information and Communication Technology (ICT) solutions are being implemented within the building structures. The technological advancements in ICT solutions have the potential to reduce carbon emissions effectively. BEE has developed a 'national strategic plan for energy efficiency' to harness India's energy efficiency potential. In this plan, annual energy audits of buildings by BEE suggests that existing building structures have a potential of 30-50% of energy savings. For new building structures approved by BEE, numerous ICT solutions are being implemented. The strategic plan set by BEE has created a specific national target roadmap for next 7 to 15 years of energy savings. BEE is also exploring the 'Net Zero Energy Buildings' where the net energy consumption is nearly zero. There are multiple factors which define the energy performance of a building. Among these factors, indoor room temperature is a critical one, as it creates an equilibrium between energy consumption and maintains much-needed building comfort. The forecasting of indoor room temperature holds a key in the building's energy forecast for an approximate estimation of the

futuristic heating and cooling demand (Mateo et al., 2013). It provides essential information about meeting the in-future energy demand. In addition, forecasting indoor temperature provides an information about the prospective peak load hours when high indoor room temperature profile will lead to high cooling load demand, which would lead to peak usage of HVAC controls. Thus, this forecast would guide the building management system to be prepared for the prospective peak hours' usage. This can be accomplished through a feedback control loop using controllable actuators, which work in the 2-step process: 1. Low load cycle, 2. Heavy load cycle. The stored energy during low load cycle can be discharged during high cooling demand, which is predicted using forecasted temperature profiles. Thus, through this feedback control loop, the short-term hourly forecast of indoor room temperature can effectively optimize the peak load demand and futuristic actions can be planned in time. It has been suggested that to maintain the building comfort and to minimize the power consumption, temperature prediction becomes significant so as to accommodate the building solace as well as it helps in efficiently controlling the HVAC usage accordingly (Zamora-Martinez et al, 2013).

Research Motivation: The indoor temperature forecasting has garnered increased interest among researchers, considering the impact it creates to the final sustainable outcome of a building structure, which in turn, results in efficient controlling mechanism for the HVAC systems of the buildings. Researchers are working on the novel concepts and designs for efficient and greener buildings where the methods of optimized energy consumption are being evaluated. The focus of the research is to save building's energy and environment through greener solutions, and particularly through indoor temperature forecasting. It is imperative that adoption of new emerging technologies, novel predictive tools development, increasing awareness and exposure of people towards government's energy related policies and programs and increasing awareness towards the importance of saving energy would help in making India an energy secure nation. For a developing country such as India, considering energy,

sustainability aspect is an important goal. The sustainability goal also suffices the United Nations (UN) Sustainable Development Goals (SDG) Vision 2030 with Goal number 11 (UN SDG, 2015), which is categorized as 'Make cities and human settlements inclusive, safe, resilient and sustainable'. This statement is the principal motivation of this thesis work where the novel energy predictive tools have been developed which would help India achieving a status of self-reliant and energy resource efficient nation. In India, building classifications include residential, commercial, and industrial buildings. In India, air-conditioning and space cooling contributes to 31% of the total energy consumption in commercial buildings (BEE report, 2020). The scope of this thesis work is related to commercial buildings only, because this work refers to the development of novel predictive tools for optimal energy consumption pertaining to the heating and cooling load demands coming from HVAC systems which is very prominent in commercial buildings space.

For any building structure, there are multiple factors that affect the heating/cooling load forecasting, such as indoor temperature and humidity, indoor carbon dioxide (CO_2) concentration, indoor air quality with pollutants, external environmental factors, cooling, or heating capacity as well as location of the building. Out of these factors, forecasting of indoor temperature profile gives much accurate and reliable energy load demand forecasts (Mateo et al., 2013). A reliable and accurate indoor temperature profile forecast leads to an efficient energy load forecasting, which in turn, leads to energy savings because using these forecasts for a building or cluster of buildings, whole Building Management System (BMS) can optimize their distribution process. On other hand, this way the BMS can also provide a feedback to utilities distribution unit as well as generation unit for optimum energy requirement needs. This prevents losses and improves the efficiency of the whole system. Another aspect of indoor temperature forecasting leads to an approximated information about the on peak, as well as off-peak demands. The on peak as well as off-peak demands, in turn, give a fair understanding when there would be a maximum or minimum heating or cooling load demand, which enable

BMS and utilities provider well prepared for the light and heavy usage from the building's occupants. The stored energy during the off-peak cycle can be discharged during high cooling demand. Thus, the short-term hourly forecast of indoor room temperature can effectively optimize the peak usage well ahead in time for futuristic actions. The incorporation of these forecasts, in association with new and emerging technologies such as machine learning and internet of things (IoT) approaches, are going to benefit building structures in India immensely, thus providing the motivation for this research work.

Research Challenges: Within Indian context, the development of indoor room forecasting predicting tools is at a nascent stage. Literature suggests that there are very limited cases pertaining to indoor room temperature forecasting, considering Indian climatic and geographical conditions. Being a developing country, with limited electrical energy resources available, rapid energy consumption in building structures, due to rapid urbanization and population growth, is a big problem. To address this problem, superior Building Energy Management Systems (BEMS/BMS) need to be designed which can help in accurate energy load forecasting. As per literature, various feedback, need, or occupancy based smart indoor temperature prediction models are available, which are either one step ahead or very short horizon forecasting models. Though the need or occupancy-based HVAC systems can sense and react in few minutes to adjust the room ambience, a need for significant time horizon short-term indoor temperature forecasting from 24 to 48 hours is necessary for the efficient and long-term regulation of energy appliances or HVAC devices. Futuristic smart actions based on the forecasting would result in increasing the operational efficiency of building structures, thus playing a pivotal role in mitigating the climate change impacts, which in turn would help in achieving sustainable goals. Often, the development of these types of models are accuracy driven models and do not consider the facts around the run-time performance and cost involved in model development and implementation. In this thesis, a variety of statistical models motivated by the data-driven approach, using conventional and Bayesian theory have been

proposed for indoor room temperature forecasting. This thesis is also motivated by the emerging machine language approaches for complex non-linear forecasting problems and incorporates neural networks and support vector machines to develop novel time series forecasting framework.

The availability of many variables affecting the indoor room temperature presents a research challenge for developing a suitable predictive model. The identification of the influencing variables presents a challenging task as it influences the accuracy and run-time performance of the predictive model. Considering all the factors affecting the indoor room temperature forecasting, building a model with short-term forecasting range with fair accuracy, is a formidable challenge. Moreover, the available literature lacks in theoretical approach, demonstrating the relationships between the forecasted and the explanatory variables. In addition, the run time performance of the predictive tools is an important aspect to consider for their real-time implementation in the environment. Accuracy of any forecast model has always been an important criterion for its development. The implementation of standard (conventional) and Bayesian approaches for time series forecasting and quantification of the best approach under given conditions results into an appropriate usage of each methodology. Also, since these models are based upon machine learning approaches, the run time performance of each methodology is an important aspect, considering their real-time implementation in the field. Moreover, building ICT solutions related to forecasting models for multiple buildings always remain a costly affair considering the collection of real-time weather (external) and indoor building (internal) data through sensors. Processing, storing and analysis of the huge real-time data presents a challenging task. So, there is a formidable research challenge to develop an accurate, easily maintainable, and adaptive systematic mathematical forecasting model using less training data from a particular building and generalizing the results for similar structures.

Model Predictive Control is a proven methodology which is being currently used by several industrial applications. Considering indoor room temperature forecasting for next 24

hours with certain internal and external factors, building of a closed loop predictive control system is a challenging task. An objective function is being proposed to demonstrate the MPC effectiveness in reducing the building's energy demands and thus energy costs, while maintaining the thermal comfort within limits. This would be achieved through various simulations done on a virtual model with data inputs from real world.

Literature Review for Indoor Temperature Forecasting: The timeline of the references is divided into two parts.

- The important semantic and pioneer works related to indoor temperature forecasting have been taken into consideration for three decades, from 1971-2000.
- Latest advancements and the state of art work in the field of indoor temperature forecasting have been taken into consideration for last two decades, from 2001-till 2021.

Peer-reviewed journal articles, conference papers, reference books and PhD theses have been searched using the Google Scholar, Science Direct and Scopus search engines, from year 1971 till 2021 for indoor temperature, heating and cooling load forecasting. From the Keywords such as 'indoor temperature forecasting', or 'building energy forecasting' or 'machine learning methods for heating and cooling load forecasting using indoor temperature' have been used for the keywords search to search Elsevier, Emerald, Sage, Taylor & Francis, Springer, World Scientific and J-STOR databases. From the list of references, below information has been compared for the critical literature review: Research objectives and details of research work conducted in the field of indoor temperature and building energy forecasting, methodology and models used, forecasted and explanatory variables used, location of study, tools used in the study and finally salient findings of the research.

Earlier Works-Timeline (1971-2000): Regarding methodologies used within indoor temperature prediction, some of the important earlier semantic works involving the data driven

approaches use regression and time series methods as the forecasting models. Parti and Parti (1980) proposed, one of the first method for building's energy consumption where linear regression was used. Forrester and Wepfer (1984) proposed the MLR methodology as a simple and easy way to predict loads in large commercial buildings. ARMAX models were also discussed by Crawford and Woods (1985) where these models were used for electric heating controlled single-family residences. Norlen et al (1987) developed linear regression (ARX) model for thermal parameters of two well insulated test cells. Rabl (1988) proposed various thermal as well as building's data driven methodologies for energy usage dynamic analysis and parameters estimation in buildings. Year 1995 onwards earmark a paradigm shift in building energy and indoor temperature forecasting, from the statistical methods such as regression or stochastic time series, to the advent of neural networks. Curtiss et al (1995) demonstrated the usage of neural networks to optimize energy consumption in a commercial-scale Heating, Ventilation and Air-Conditioning (HVAC) system, where information from an actual system has been used to train the neural network for efficient energy optimization, vis-à-vis maintaining thermal comfort. Kah et al. (1995) used a neural network, to control a bus's temperature. Kajl et al. (1997) proposed a fuzzy-neural network for simplified and detailed estimation for a building's energy consumption. Kalogirou et al (1997) presented heating load estimation of a building using artificial neural networks using minimum input data. Kalogirou and Bojic (2000) used ANNs for the prediction of the energy consumption of a passive solar building for both summer and winter seasons.

Latest Advancements-Timeline (2001-2021): Pederson (2007) has cited three methodologies for building energy and load forecasting: Statistical approaches (linear or multivariate regression analyses), Energy simulation programs and Intelligent computer programs. Zhao and Magoules (2012) have documented five major groups for prediction methods: Engineering methods, Statistical methods, Neural networks, Support vector machines and Hybrid/Grey models. Foucquier et al. (2013) suggested three broad categories: Physical models, Statistical

methods, and Hybrid models. Fumo (2014) classified various approaches of building energy estimation procedures into five major categories: Regression, Intelligent, Hybrid, Forward and Calibrated/Simulation based. Mat Daut et al. (2017) conducted a detailed review of the performance of conventional and artificial intelligence forecasting methods for building's energy consumption. In recent times, hybrid models have gained importance in forecasting domain. Machine learning has gained lot of significance due to fast adaptation to growing and complex volume of data. It has several advantages such as: novel simulation ways for large data, extensive computational capabilities, data-iterative learning, finding hidden insights and efficient generalization. different data driven approaches have been demarcated into linear, non-linear, and hybrid models (Amasyali and El-Gohary, 2018). Data driven techniques have been divided into two sub-categories: a) Single forecasting models which use a single algorithm for forecasting processes and b) Combined forecasting models which use a framework of combination of single algorithm techniques and optimization methods (Bourdeau et al, 2019, Mat Daut et al, 2017, Ahmad et al, 2008). Single forecasting models are further divided into linear and non-linear forecasting models. The data driven, statistics and regression-based models are linear models which include Multiple Linear Regression (MLRs), Auto-Regressive (ARs), Bayesian Dynamic Models (BDMs) and Moving Average and Exponential Smoothing (MA & ES) forecasting models. The non-linear models are fuzzy models, Grey models (GMs)/Grey prediction (Deb et al, 2017) and machine learning approaches. The machine learning models (Seyedzadeh et al., 2018) are also known as artificial intelligence techniques (Fumo, 2014) and intelligent computer systems (Pedersen, 2007). Mateo et al (2013) used Auto-Regressive methods, linear regression and neural network machine learning models for indoor temperature forecasting for a building located in Málaga (Spain). The explanatory variables used are: Month, Weekday, Day of the month, Official Time, Outdoor Temperature, Outdoor Relative Humidity, Set Point Temperature, Power. The hybrid forecasting model of Multiple Layer Perceptron – Non-linear ARX (MLP-NARX) resulted in most accurate model

with reported Mean Absolute Error (MAE) as 0.111. Zamora Martinez et al (2013) developed time series forecasting models using Exponential Smoothing methods (ETS), Auto-Regressive Integrated Moving Models (ARIMA) and neural network models (ANNs) to predict indoor temperature for Single-Medium-Large system house. The study conducted in the house built in the Universidad CEU Cardenal Herrera, Spain. The explanatory variables used are: Hour of the day, Solar Irradiance, Indoor Relative Humidity, Indoor Air Quality, Rainfall. Here also, combined forecasting model of ARIMA + ANN resulted in the best fit model.

Literature Review for Model Predictive Control Mechanism: The focus of today's research is to save building's energy and environment through greener solutions. It is of vital significance to execute novel control designs that, from one perspective permit the energy enhancement of HVAC frameworks without disregarding the warm solace of building inhabitants and then again offer to the strategy creators and residents an intelligent device for the observing and control of the HVAC framework (Carli et al, 2020). In recent years, Model Predictive Control (MPC) has gained importance in the research community due to its quick ability of inclusion of constraints and disturbance variables, as well as fast dynamic control. Being a developing country, Indian buildings need such research to be conducted to channelize its energy needs properly, checking the unnecessary energy wastage, thus reducing carbon emissions. Moreover, reduction in smart devices' costs with sequential advancements in Information and Communication Technology (ICT) have resulted in an environment where MPC control strategies can be easily implemented for energy and occupants' thermal comfort optimization (Serale et al, 2018). In MPC, solution of an optimization problem is solved over a given time horizon through calculations of optimal control inputs to the system (Morosan *et al*, 2010). There are several factors necessitating the development of optimized control of heating/cooling and lighting systems. Indoor room temperature, indoor humidity, and illumination forecasting results in significant energy savings, keeping in mind that, during peak usage cycle, occupants' comfort levels are maintained and are not violated significantly (Agheb

et al, 2015). Optimum control of heating/cooling units and lighting systems, though, results in significant energy savings, but a well-balanced trade-off needs to be maintained between the two. The discomfort levels should not be such that one achieves the energy savings targets but on the cost of highly dissatisfied user comfort.

Research Gaps: Based upon above mentioned research challenges and critical review of the literature work done, identified research issues have been mentioned below:

1. There are limited reported cases pertaining to indoor room temperature forecasting considering Indian climatic and geographical conditions.
2. Available feedback control systems in current buildings are need or occupancy based smart temperature control. There is a limited presence of forecasting tools which can forecast the indoor room temperature for a significant time horizon window (n>=24 hours).
3. Existing literature mainly points towards the accuracy part of the developed mathematical models but lack in theoretical modeling, performance, or cost involvement of the models.
4. Very limited work has been conducted on indoor temperature forecasting using Bayesian inference or Bayesian state space modeling which uses posterior probability distribution.
5. Expectation Maximization (EM) algorithm is a forward-backward algorithm and is described as an algorithm which is used to efficiently compute point estimates and is used to obtain the desired posterior distribution. EM algorithm is efficiently used for the latent variables. These are those variables which are not directly observable or hidden from the view of the users. The algorithm is useful where the underlying time varying state space variables are assumed to be hidden. There has been no work done in Bayesian state space modeling using EM algorithm for building's energy forecasting using indoor temperature profile.

6. Combined forecasting approach or hybrid modeling approach in indoor room temperature forecasting has been harnessed to a limited extent, due to the complexity involved during the model development. Existing literature references point towards this significant research gap.
7. Although numerous previous studies on MPC strategies for energy consumption and thermal comfort optimization have been conducted, these studies have been confined to the use of three or at most four disturbance variables. The presented study incorporates five disturbance variables into the control mechanism thus making it more accurate. Also, the previous studies on MPC strategies mostly consider ARMAX models for finding the predictor model relationships. Presented thesis uses Seasonal ARMAX (SARMAX) predictor model for MPC development.

Research Objectives: Following research objectives have been highlighted for the current thesis work:

1. **Development of Systematic Mathematical Forecasting Models using Linear Forecasting Models and Bayesian Inference:** Development and comparison of mathematical models based upon conventional linear time series models (Box and Jenkins, 1976) and probabilistic Bayesian Dynamic Modeling approach for short term indoor temperature forecasting, considering India climatic and geographical conditions.
2. **Development of Systematic Mathematical Forecasting models using Non-linear and Hybrid Models:** This research objective is further divided into two sub-objectives.
   Development of Non-linear Models: Two non-linear forecasting models are formulated, which improves the accuracy of the forecasting models. In the proposed work, non-linear forecasting models such as ANNs and SVRs are used as the non-linear machine learning models and the accuracy, run-time performance and cost effectiveness of the non-linear models are compared across with the linear models.

Development of Hybrid Models: The combined forecasting or novel hybrid time series forecasting framework has been proposed and models have been developed using linear and non-linear models obtained from above two objectives respectively. These hybrid models have been developed, both for the conventional Box-Jenkins models as well as Bayesian state space models.

3. **Multi-Variate Model Predictive Control for Smart Buildings:** As part of this thesis work, only simulation-based development of multi-variate model predictive control (MPC) has been done. Based upon the understandings gathered through linear model development in objective 1, a categorization of the internal and external factors having maximum influence on the indoor temperature forecasting has been done. Post this categorization, a simulation based optimal energy consumption model control has been developed with an objective function which optimizes the energy consumption within a building structure keeping thermal comfort within acceptable limits.

Research design and methodology: This quantitative study has been conducted in two cities of India, i.e. Bhubaneswar and Bengaluru, considering Indian climatic, geographical and building characteristics. A selective list of sixteen explanatory variables impacting the indoor room temperature profile is selected and used to develop forecasted and explanatory variables relationships using data driven approach where different time series forecasting techniques have been developed. A 3-step variables selection approach has been adopted to come up with the selective list of sixteen explanatory variables. The first step is the 'Selection' method where an exhaustive list of 26 explanatory variables impacting indoor temperature forecasting has been selected from several research works done in this domain. These explanatory variables have their presence both internal and external to the building structures. These explanatory variables are broadly categorized into four parts, 1. External environmental factors, 2. behavioural factors, 3. Internal building control factors, and 4. Building characteristics. The second step of variables selection process is the 'Expert Panel Brain-Storming Sessions' where

brain-storming sessions are conducted in association with experts from academics and industries to filter out most contributing explanatory factors. After step two process, the number of explanatory variables are reduced to 21. In the third step, dimensionality reduction process is performed using Principal Component Analysis (PCA) methodology where eigen vectors and values are calculated for the explanatory variables obtained from second step. Based on PCA results, most contributing 16 explanatory variables are chosen for the final analysis. In this way, both exploratory and quantitative approaches using software packages have been sed to funnel out the contributing explanatory variables. The linear time series forecasting methodologies adopted in the objective 1 research design are Box-Jenkins methodology based ARIMA and ARIMAX models. ARIMA and ARIMAX models have been considered in this thesis work because these are standard time series models and have been used as baseline models for the accuracy and performance comparison with other models which. These models help in building closed-form relationships with respect to thermal model characteristics of the building. On the adverse side, these models follow a basic assumption where the time series parameters once determined, are assumed to be constant over time, which may not be a fair assumption considering indoor temperature profile forecasting because the dynamics of indoor temperature may be influenced dynamically by external factors. As a result, Bayesian modeling has gained importance because of its advanced and alternative approach of data modeling, while handling highly dynamic time series phenomenon. So, in the current research design, Bayesian inference-based BDMs and BDMEx are the other two linear forecasting methodologies adopted in this thesis.

Since, indoor room temperature forecasting is an hourly scale forecasting, there is a probability that linear time series models, presented in objective 1 may not be able to capture the non-linear dynamicity of the highly non-linear time series phenomenon. The research design framework of objective 2 points towards the inclusion of non-linear forecasting models and hybridization with the linear forecasting models to increase the accuracy of the resulting

forecasting models. Out of several non-linear forecasting models, ANNs and SVRs have been chosen for the current study, because both these advanced machine learning approaches are simpler and accurate, considering the fitment of the training dataset and are mostly used for several time series forecasting applications (Seyedzadeh et al, 2018). The research design framework for objective 2 also incorporates a novel hybrid modeling approach where the linear forecasting models from objective 1 have been hybridized with non-linear forecasting models from objective 2 to result in better fitting and more accurate time series framework, which utilizes the benefits of both linear and non-linear forecasting models. These models are categorized as ARIMAX-ANN, ARIMAX-SVR, BDMEx-ANN and BDMEx-SVR. A detailed accuracy, run time performance and cost implication analysis has been conducted for all of the forecasting models. Each of these models have its unique characteristic, whether it is accuracy, run time performance or cost implications. The use of these 10 forecasting models can vary depending upon the application areas they are going to be implemented. Based upon objective 3, considering Indian climatic, geographical and building characteristics, a research design framework for Model Predictive Control mechanism (MPC) is adopted, where a dual objective function of energy optimization vis-à-vis thermal comfort has been simulated using five disturbance variables, such as outside air temperature, outdoor relative humidity, solar irradiance, wind speed and rainfall. A Seasonal ARMAX (SARMAX based temperature and humidity control and regression based illumination control predictor models have been simulated with three control variables as input cooling power and lighting power load and roller blind positions for three optimized output variables such as indoor room temperature, humidity and illumination.

Data collection:

The data has been collected from two Indian cities – Bhubaneswar and Bengaluru thus representing the generalized modeling approach. For Bhubaneswar city, one full year hourly

secondary dataset has been collected. The environmental and climatic data has been collected from April-2017 till March-2018, comprising of outdoor explanatory variables such as ambient air temperature, relative humidity, solar irradiance, precipitation, wind speed and direction, cloud cover etc. has been collected from Indian Meteorological Department (Indian Meteorological Department (IMD) Dataset, 2017- 2018). Average daily Air Quality Index (AQI) secondary data has been collected from State Pollution Control Board (State Pollution Control Board, Odisha, 2017 Report). The training indoor room temperature, indoor relative humidity and cooling load data has been collected from a corporate Information technology (IT) building's room (Energy Conservation Building Code (ECBC), 2017). The occupancy profile for the study has been taken static and has been explained in later chapters. The building constructional characteristics of the building has been assumed homogenous and have been taken from ECBC, (2017). For months with 30 days, 720 hourly sample data points have been taken for each month and divided into 600 data points (83% per month) for model training purposes and remaining 120 hours (17% per month) for testing and validation purposes. For months with 31 days, 600 days data points are used for training purposes and 144 dataset points for validation. Since all these data points have different units of measures (UoMs), standardization and normalization of the dataset has been done before feeding them into the models. Before starting the work on the detailed analysis, a pilot sample data collection and data analysis was done for smaller datasets of Bhubaneswar city for the months of April-2016, October-2016 and December-2016. For Bengaluru city, 6 months hourly secondary dataset (environmental, climatic (Indian Meteorological Department (IMD) Dataset, 2018), air quality (State Pollution Control Board, Karnataka, 2018 Report) and building indoor datasets (ECBC, 2017)) has been collected from April-2018 till September-2018. The purpose of choosing different months datasets for both the cities is to longitudinally generalize and validate the methodology over different times of the year. Certain constants, such as thermal conductivity, heat capacity, thermal resistance and insulation details for a corporate building and are used in

the calculations have been taken from Energy Conservation Building Code (ECBC), 2017). The occupancy profile for the study has been considered static and has been taken from ASHRAE 55 (2004). Similarly, the building constructional characteristics of the building has been assumed homogenous and have been taken from ECBC, (2017).

Theoretical Contributions: This thesis provides significant theoretical contributions to:

1. Usage of Bayesian Dynamic Models (BDMs) in the field of indoor temperature profile forecasting. Inclusion of EM algorithm is a significant contribution to theory.
2. Formulation of Seasonal Auto-Regressive Integrated Moving Average (SARMAX) based models for indoor temperature profile forecasting.
3. Formulation of SARMAX based models for Model Predictive Control (MPC) mechanism.
4. Inclusion of hybrid forecasting models is a significant contribution to theory.

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